Geographical proximity and renewable energy diffusion: An empirical approach

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ABSTRACT

In an era where achieving both economic growth and environmental sustainability is paramount, the role of technology diffusion remains an important one. Recent literature explores the link between geographical proximity and the adoption and diffusion of climate change adaptation policies. However, it has generally focused on a restricted set of developed countries and focused on the diffusion of policy instrument rather than the outcome of the policies. In this paper, we argue that domestic intensity of adoption of renewable energy technologies is likely to be affected by the adoption pattern in neighbouring countries. Additionally, this effect is likely to be stronger when important trade partners are intensive adopters of renewable energies. To test these hypotheses, we construct an index that captures a distance-weighted measure of intensity of renewable energies in other countries and apply a fixed effects framework to a panel of up to 116 countries over the (1980–2012) period. Our results confirm the existence of a geographic spill-over effect on the intensity of adoption of renewable energy technologies. Moreover, this effect is stronger when intensive adopters of renewable energies are also important trading partners, highlighting the relevance of trade channel as a potential catalyst of the diffusion of renewable energies across countries.

1. Introduction

It is now beyond dispute that the diffusion of new technologies is crucial in a number of ways. Different patterns in the diffusion of technologies have been shown to be an important determinant of total factor productivity (TFP) (Caselli and Coleman, 2001; Ertur and Koch, 2007; Jerzmanowski, 2007; Keller, 2010). Barriers to technology adoption is one of the key factors of differences in per capita income across countries (Parente and Prescott, 1994). Specifically, Comin and Hobijn (2010) find that variations in technology adoption can explain approximately 25% of cross-country income differences. Thus the geographic scope of technology diffusion across national borders can have important implications on national comparative advantages and long-run competitiveness (MacGarvie, 2005). Given their importance for economic growth, analyses of patterns of technological diffusion has attracted a lot of attention, with a number of technologies in areas such as telecommunications, transportation and industry being considered

(Comin et al., 2012).

The role of clean technology diffusion in achieving both economic growth and environmental sustainability has continued to receive attention in international climate policy debates. The successful and widespread adoption and diffusion of renewable energy technologies are important factors in increasing the sustainability of the global energy landscape. In addition, there is a broad consensus that renewable energy (RE) technology transfer is associated with not only climate change mitigation and resilience efforts, but also with economic outcomes such as energy security and job creation (REN21, 2015). Recently, cross-country technological diffusion to achieve climate-related objectives has been important for the design of "climate clubs" (Vega and Mandel, 2018), which aim to increase gains from linkages and cooperation among a small group of countries. As such, understanding the drivers of diffusion of renewables appears as an important and timely question.

So far, the literature on the diffusion of renewable energy

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technologies has highlighted a number of important domestic and international determinants of adoption such as income level, domestic energy consumption, renewable energy policies and availability of finance (Aguirre and Ibikunle, 2014; Carley, 2009; Chandler, 2009; Pfeiffer and Mulder, 2013; Popp et al., 2011). The likelihood of adopting cleaner sources of energy depends both on domestic factors and on cross-country policy diffusion. This pattern of diffusion can be induced by competition, imitation or policy learning from neighbouring countries sharing similar geographic, socio-economic, cultural and political factors (Berry and Baybeck, 2005; Gray, 1973; Massey et al., 2014; Matisoff and Edwards, 2014; Shipan and Volden, 2008; Stadelmann and Castro, 2014; Walker, 1969). To date, some elements of the link between geographical proximity and the diffusion of policies fostering the adoption of clean technologies have been studied (Matisoff, 2008; Schaffer and Bernauer, 2014). However, the link between geographic proximity, trade and the intensity of adoption of renewable energy technologies has not been adequately examined. Understanding the spatial patterns of diffusion of green or climate-friendly technologies is not only important from an academic perspective but also from a policy perspective. In theory, there are reasons to believe that the spatial diffusion is more ambiguous in the case of renewable energies.

There are at least three possible reasons why geographical proximity is likely to be important in explaining the observed patterns in the diffusion of renewable energies. First, technologies typically emerge in a specific geographic location or initial markets and it is impossible for technologies to travel beyond their origin without knowledge spreading first. Bento et al. (2018) show that knowledge spillover in energy technologies from innovators to late adopters reduces the uncertainty period associated with new technology before mass commercialisation. A number of authors argue that repeated human interactions favour the diffusion of knowledge (Boschma, 2005; Portes and Rey, 2005; Lutz, 1987) and it is believed that human interaction decays with distance (Audretsch and Feldman, 2004; Comin and Hobijn, 2004; Comin et al., 2012). As Von Hippel (1994) and Boschma (2005) illustrate, innovations with a higher degree of tacit knowledge, i.e not easily standardised, codified or transmitted via prototypes depend to a large extent on face to face interactions and communication, which are facilitated by geographical proximity. Even for codified knowledge, the assimilation process of new technology may still require tacit knowledge and thus, spatial closeness is an important factor (Howells, 2002).

A second channel is related to the risk and uncertainty associated with the adoption of a new policy. Being able to observe, exchange information and learn from the adoption process and its success in a comparable environment is likely to increase the likelihood of adopting the policy (Smith and Urpelainen, 2014). Since, in general, countries closer to each other tend to be more similar, witnessing the success of a policy in a nearby country may be a better indication of the domestic implications of the policy. In this sense, neighbouring countries can be seen as laboratories for policy experimentation (Dobbin et al., 2007; Matisoff, 2008). In the case of renewable energies (especially solar and wind), this is likely to be true as neighbouring countries may have a similar potential. Thirdly, adoption of renewable energy technologies has been found to be associated with positive socio-economic spillover effects, such as employment and investments. This implies that the adoption of these technologies may influence the decision to adopt in neighbouring areas as a result of competition for markets, especially if adopting countries are also main trading partners (Schaffer and Bernauer, 2014; Shipan and Volden, 2008).

However, in the case of renewable energies, the relationship is, at least in theory, more ambiguous for four main reasons. First, as mentioned in Ausubel et al. (1998) taking transportation as an example, the wheel represented an improvement compared to travelling by foot and motor cars also represented an improvement in terms of efficiency and time-saving compared to horses. In the case of renewable energies, while renewable energies are desirable from social and environmental

perspectives, they may not always be the most economical option to increase electricity supply (especially in oil-rich countries). Moreover, certain renewable energies may also be associated to some specific challenges, such as intermittency and energy storage. Second, energy systems could be characterised by path dependence, where inferior technology can persist because of the lock-in effect resulting from factors such as public policy, rent seeking, and economies of scale (Verdolini and Galeotti, 2011; Unruh, 2000). Third, in the case of renewables, the feasibility of adopting renewable energies is often constrained by the natural endowment of the country. Fourth, since the diffusion of renewable energies is currently on-going, it is unclear whether the speed of diffusion of the renewables will conform to the often-observed S-shaped curve that characterises the speed of adoption of a technology over time.

Previous literature has mostly focused on developed countries (USA, EU, OECD) and on the diffusion of policy instruments rather than on outcomes (i.e electricity generation from renewable sources). To our knowledge, there was no previous attempt that investigates the spatial diffusion of intensity of renewable energy using a global sample and how this diffusion changes over time and with increased contact (through trade) with intensive adopters. In order to investigate this, we construct an index, similar to Comin et al. (2012), that captures a distance-weighted measure of intensity of renewable energies in other countries. We use a fixed effects estimator using a panel of 116 countries over the 1980–2012 period.

Our findings contribute to the literature on adoption of renewable energy technology and to our understanding of how geographical proximity plays a role in the diffusion process. Moreover, in the context of climate change mitigation and adaptation, the paper sheds light on how spatial patterns could shape convergence towards sustainability transitions across the globe. Our results highlight the fact that the scope of diffusion of renewable energy technologies like other types of technology has a spatial aspect. Spatial interdependence does matter in the process of technology adoption/diffusion. We find a positive and significant effect (at the 1% or 5% level) of geographical proximity to adopters on the diffusion of renewable energies. However, we do not find strong support for the hypothesis that this effect increases over time. The results also show that, in addition to a positive spatial diffusion of intensity of renewable energies, this effect is stronger when important trade partners are also intensive adopters of renewable energies. This highlights the relevance of trade links with adopters of renewables as a catalyst of the diffusion of renewable energies, especially in low-income countries.

The rest of the paper is structured as follows. In section 2, we briefly describe recent trends of renewable energy diffusion and the main literature findings on drivers of policy adoption and technology diffusion. Methodology and data are described in section 3. We present the estimation results followed by a discussion of our main findings in section 4. Finally, section 5 concludes.

2. Diffusion of renewable energy

2.1. Recent trends of renewable energies: a brief overview

The number of people without access to electricity fell from 1.7 to 1.1 billion between 2000 and 2016 (IEA, 2017). Despite this, fuel and energy poverty remain important issues in a number of countries, where increases in energy prices lead to an increase in fuel poor households (Walker and Cass, 2007).

In recent years, however, renewable energies have become increasingly important in the energy landscape, with 34% of new connections being provided by renewable energy sources (IEA, 2017). In some countries renewable energy technologies are progressively replacing traditional carbon-intensive sources and investments in renewables have recently surpassed that of fossil fuel and nuclear power combined (REN21, 2018). In addition to this, they are also increasingly

crucial to a wider range of environmental, social and economic goals. In a number of developing countries, low incomes often lead to a lack of access to cleaner fuels, perpetuating a dependency on polluting fuels (Pachauri et al., 2004), which have adverse effects on health and productivity (Ekholm et al., 2010; Pachauri and Spreng, 2011).

However, renewable energies are also seen as part of the solution for a number of reasons. First, the current trends in costs of renewable energies could enable countries to hedge against the variability and uncertainty of fossil fuel prices. Second, renewables could lead to an improvement in the access to affordable modern energy. Off-grid systems (e.g. solar home systems), in particular, could represent a solution for those households in areas that are hard-to-reach in the national grid (Barnes et al., 2011). Finally, a transition to cleaner fuels could also lead to health and productivity improvements, which could act as a catalyst for broader human development (Pachauri et al., 2004; Ekholm et al., 2010; Pachauri and Spreng, 2011).

The pattern of investments in the energy sector has also changed significantly in recent years. Renewable energy technologies emerged initially in a few number of developed countries who were engaged in research and development of new technologies. As pointed out by Dechezleprêtre et al. (2011), climate-friendly innovations remained mainly concentrated in OECD countries, especially in Japan, US, Germany and China, which accounted for 67% of the world inventions during the 2000–2005 period. More recently, middle-income countries such as China, Brazil and India, have invested heavily in renewable energies. According to a recent report, developing and emerging countries had higher levels of renewable energy investments in 2017 than developed countries, accounting for 63% of global total investment (REN21, 2018).

2.2. Policy adoption and technology diffusion: theoretical framework and empirical evidence

2.2.1. Theoretical background

In many respects, changes in adoption pattern for green technologies are likely to be similar to that of technology more generally (Allan et al., 2014; Stoneman and Diederen, 1994). To understand the way in which the diffusion process of innovations unfolds, several studies have examined technology adoption and policy diffusion from different perspectives; historical, behavioural, and economical (Hall, 2004). There is consensus that the adoption pattern of a technology or policy follows an S-shaped curve, which implies that no technology has been adopted by all potential users at the same time.

The S-shaped diffusion pattern is generally used to describe how a new technology is adopted at first by few users and then rapidly increases, until at some point, adoption rates fall as the number of remaining potential adopters decreases. Geroski (2000) presents three theoretical models and the channels that can provide an explanation to the observed S-shaped. In the "epidemic model", access to information about the technology and the interaction between adopters are the driver of the S-shape. The "probit" model is related to differences in the characteristics of adopters and potential adopters. These differences include taste, expected returns to adoption, and the relative cost of adoption. The third model, known as "legitimation and competition model", hypothesises that once a new technology becomes accepted, competition for resources and markets for goods and services using the new technology tend to diminish returns for early adopters. This consequently lowers expected returns by non-adopters and slows the rate of diffusion over time. It is worth emphasizing that these three types of theoretical models are not mutually exclusive.

In terms of mechanisms for policy innovation and diffusion, there are three main mechanisms identified in the literature. The first mechanism occurs through learning from peers, whereby a policy maker will observe and learn from experiences in neighbouring countries/regions. This mechanism has two main advantages. First, the effects of policies in neighbouring countries are policies perceived to be a useful

source of information regarding the policy and its likely consequences in-country (Gray, 1973; Massey et al., 2014; Shipan and Volden, 2008; Smith and Urpelainen, 2014). Second, learning from neighbours about policies or technologies lowers the fixed costs associated with learning about the technology (Feder and O'Mara, 1982; Griliches, 1957; Rogers, 2003).

The second diffusion mechanism, imitation or emulation, refers to copying the actions of peer states and is used to describe the adoption of innovations with a high degree of uncertainty regarding its costs and benefits (Biesenbender and Tosun, 2014). Generally, peer states will either be recognised as being pioneers, would share ideological predispositions, or would be geographically close (Berry and Baybeck, 2005; Lyon and Yin, 2010; Matisoff, 2008; Nicholson-Crotty, 2009). Boschma (2005) argues that geographical proximity is neither necessary nor sufficient for the transfer of innovations, but it facilitates learning and transfer of knowledge. In addition, geographical proximity is often correlated with institutional proximity, as well as certain geographic characteristics important for renewable energies (e.g. annual average of solar radiation).

The third mechanism is through competition, where theorists argue that competition for trade and capital drive states to adopt innovative policies or technologies to gain competitive advantage over proximate states (Berry and Berry, 2007; Boehmke and Witmer, 2004; Massey et al., 2014). As such, countries are likely to adopt the policy if there are positive spillovers from that policy to nearby states (Shipan and Volden, 2008). One common aspect across these mechanisms is that in all mechanisms there is a geographical aspect to the adoption and diffusion of a certain policy or technology.

2.2.2. Empirical evidence on the link between diffusion and geography

Empirically, studies on technology diffusion have highlighted the role of geographical proximity to adopters on the intensity of domestic diffusion of technology. According to Ciccone (1996), technological interdependence across countries exist, implying that the aggregate level of technology in a country does not only depend on domestic factors, but also on the level of technology of neighbours (see Caselli and Coleman, 2001; Ciccone, 1996; Comin et al., 2012; Keller, 2002, 2004) with an intensity which decreases with distance (Ertur and Koch, 2007). Comin and Hobijn (2004) and Comin et al. (2012) find that geographical proximity to early and/or intensive adopters leads to an increase in the intensity of adoption of a given technology. This result is consistent across a set of 20 major technologies using a sample of 161 countries. The authors postulate that this positive spill-over occurs as a result of knowledge transfer from adopters to non-adopters. The knowledge transfer itself is made possible by the interaction between users and non-users of a technology and probability of interaction is assumed to be increasing with geographical proximity. Keller (2002) finds that geographic distance between countries matters for industry productivity gains. The author finds that an additional 1,200 km between two countries is associated with a 50-percent drop in technology adoption, presenting evidence that technology diffusion is geographically localized. The findings also support the hypothesis that localization of diffusion tends to decrease over time.

Authors have also used patent citations as a proxy of knowledge spillover to test for technology diffusion determinants. Jaffe et al. (1993) test if knowledge spillovers are localized. They find that localization of knowledge fades over time as technology diffuses faster across regions and that distance matters for knowledge flows within the USA. Similarly, Eaton and Kortum (1996) looked at determinants of productivity gains in OECD countries, they found that larger geographical distance between innovators inhibits the flow of ideas between countries, while trade relationships enhances it. Using a sample across 147 sub-national regions in Western Europe and North America for the (1975–1996) period, Peri (2005) estimates that geographic distance reduces knowledge flows by 3% for each thousand kilometers travelled, in addition to 19% loss of knowledge flow if the language

between regions is different. MacGarvie (2005) uses a similar dataset on few EU countries and USA for the (1980–1995) period and find that countries which are 10% geographically closer than the average country pair have 1% more citations, however, the effect of geographical proximity diminishes over time.

Regarding energy-related innovations, there are few studies that examine the spatial aspect of technology diffusion. Vega et al. (2018) use the observed pattern of wind technology installations in 195 countries to estimate the determinants of network formation. They find that geographical proximity has a positive impact on diffusion of wind energy technology, but that this effect was statistically insignificant. Similarly, Stadelmann and Castro (2014) only find a significant effect of neighbouring countries' RE adoption on domestic adoption if the peers had the same colonial history. Verdolini and Galeotti (2011) explicitly consider geographical proximity as moderating factor for knowledge flows of energy-related innovations for 38 countries using patent citations. They find that the flow of knowledge is geographically localized and that higher technological and geographical distances decrease the probability of innovation diffusion. Bento et al. (2018) differentiate between initial markets and late adopters in their analysis of spatial diffusion of 15 energy technologies using hazard models. They find that the speed of diffusion is related to the extent of the knowledge spillover in follower markets as well as a number of technology-specific factors. The adoption of RE policy was found to be correlated with EU membership and authors argue that regional memberships facilitate horizontal policy diffusion through peer-group effects (Schaffer and Bernauer, 2014; Stadelmann and Castro, 2014). Smith and Urpelainen (2014) use the average Feed-in Tarriff (FIT) in neighbouring countries as a predictor of a countrys FIT in 26 industrialised countries. According to these previous studies, geographical proximity is an important determinant of adopting a new policy or technology.

Other studies look for alternative channels through which knowledge may be transferred. Two important mechanisms cited in the literature are trade and investments of foreign enterprises. Boschma (2005) argues that access to international trade is a way to avoid spatial lock-in. Eaton and Kortum (2002), for instance, argue that traded capital goods embody new technological knowledge and, as such, are a vehicle through which knowledge is transferred. Similar findings were found by Ferrier et al. (2016) where direct and indirect network effects of trade increased the diffusion of 24 technologies in a panel of 145 countries over the (1962–2000) period. Grossman and Helpman (1991) found that productivity increase depends on the stock of local knowledge capital which is an increasing function in the frequency of contacts with the international research and business communities. Additionally, the authors argue that an increase in the number of trade partners is likely to lead to increases in productivity since this is linked to an increase in the frequency of contacts. Caselli and Coleman (2001) find a strong association between trade openness and computer technology adoption for a panel of 155 countries spanning the 1970–1990 period.

Literature has also focused on the impact of trade openness on the adoption and diffusion of environmental-friendly technologies. For example, Vega et al. (2018) found that economic integration is an important determinant of the diffusion of wind energy technology. Reppelin-Hill (1999), using a sample of 30 countries over the 1970–1994 period, found that the diffusion of a cleaner steel production technology was faster in countries with more open trade regimes. Similarly, Wheeler and Martin (1992) found that openness enhances the speed of diffusion of thermomechanical pulp technology, a clean pulping process, in a sample of 60 countries. Overall, there is empirical evidence supporting that trade plays a role in diffusing innovations and technologies, especially when trade partners have a high knowledge stock (Coe et al., 1997; Navaretti and Tarr, 2000).

At the micro level, studies have looked at factors affecting diffusion of energy technologies. Socio-economic factors such as education, wealth and prices of substitutes are positively correlated with the use of

clean energy sources (Rahut et al., 2014, 2017; Mottaleb et al., 2017; Guta, 2018; Lay et al., 2013; Sardianou and Genoudi, 2013; Shi et al., 2013; Fleiß et al., 2017). In terms of demographics, female-headed, urban and households as well as younger household heads were found to be more likely to spend more on cleaner energy sources (Mills and Schleich, 2012; Willis et al., 2011; Rahut et al., 2017). Finally, more relevant for this paper is the literature on social, peer and geographic effects at the micro-level. Overall, peer and social effects were found to be significant in the demand for solar photovoltaic panels in the state of Connecticut and in Sweden (Graziano and Gillingham, 2015; Palm, 2017). In another study, Kwan (2012) found that the probability of installing residential solar photovoltaic is influenced by adoption in adjacent ZIP codes, which generally share similar demographics and resource potential.

However, although there are some examples of studies focusing on renewable energies, the majority of literature to date has focused on the adoption of telecommunication (telephone, computers, television, internet), transportation (e.g. Shipping, rails, aviation) and industry (tractors, ATM, electricity). Few studies have empirically examined the effect of geographical proximity to adopters on the intensity of production of renewable energies.

Importantly, renewable energy technologies may be different from other technologies in terms of the pattern of adoption. In the case of other technologies, often they represented a marked improvement on the existing technology and no substitute could deliver the same outcome at a lower cost. For example, trains and cars cannot be easily substituted by horses. In the case of renewable energies, however, there are a number of different options to generate electricity. Additionally, economic incentives to adopt renewables will depend on pre-defined geographical characteristics and natural resource endowment (e.g. wind, sun radiation) which may be correlated across space. As such, it is not clear that the same geographical pattern of technological adoption should prevail in the case of renewable energies.

As such, we test three hypotheses. First, we test whether geographical proximity to intensive adopters has an effect in the domestic intensity of renewable energies. While the expected sign is more ambiguous for renewable energies, we expect there to be a positive correlation, given that the experience neighbouring countries sharing similar characteristics often offers a good indication of the potential success of the technology domestically. Second, we test whether increased contact (through trade) with intensive adopters has a significant effect on the diffusion of renewable energies. Given the previous literature, we would expect trade with intensive adopters to be positively correlated with intensity of renewable energy domestically. Finally, we also test whether the effect of geographical proximity, if any, increases or decreases over time. For most other technologies, the literature finds a decrease in the effect over time. However, for renewable energies since the technologies have not yet fully diffused and because each individual technology may be at a different stage of maturity and associated with a different speed of diffusion, we argue that this relationship is not so clear (Bento et al., 2018).

3. Data and methodology

3.1. Data

Given that our main focus is on the pattern of diffusion intensity of renewable energies, our main dependent variable will be the per capita net production of renewable electricity (excluding hydro) in the country.[2] This variable is constructed by dividing the total renewable electricity net generation (Bil kWh) by the total population of a country

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[2] We have excluded countries that have never adopted renewable energy technologies during the (1990–2012) period as the dependent variable would be zero.

Table 1
Variable definitions and sources.

Variable	Definition	Source
Intensity	Total renewable electricity net generation, excluding hydro (Billion kWh)	EIA
Population	Total population (Millions)	WDI: World Bank
GDP per capita	Gross domestic product divided by midyear population (constant 2010 USD)	WDI: World Bank
CO_2 emission	CO_2 emission per capita(metric tons)	WDI: World Bank
Electricity consumption	Electric power consumption growth rate (%)	WDI: World Bank
Electricity from Fossil	Fossil Fuel energy consumption (% total)	WDI: World Bank
Kyoto	Ratification for the kyoto protocol (Dummy)	UNFCCC
RE policy	Adoption of RE policies and measures (Dummy)	IEA: Global RE policies and Measures
Distance	Bilateral distances between the biggest cities of two countries (1000 Km)	CEPIIs geodist database
Trshare	Bilateral flow of trade (1000 USD) as a proportion of total trade	CEPIIs TradeProd database, Authors' calculations
DIRE 1 (index 1)	The sum of intensity of renewable electricity production in country j (per capita) divided by distance between country i and country j, for all j countries	Authors' calculation
DIRE 2 (index 2)	The sum of the product of intensity of renewable electricity production in country j (per capita) and bilateral distance between country i and country j, for all j countries	Authors' calculation
Trade Index 1	Distance index 1 weighted by trade shares between country I and J	Authors' calculation
Trade Index 2	Distance index 2 weighted by trade shares between country I and J	Authors' calculation

in a given year. Empirical literature available has proposed two possible measurements for technology adoption. First, the extensive margin of adoption which measures the share of producers who adopt a given technology at a certain point of time (Audretsch and Feldman, 2004; Gort and Klepper, 1982; Griliches, 1957; Mansfield, 1961). Such measure is usually applied at the micro level. Second, the intensive margin of adoption measures the production of unit of outputs embodying the technology or the share of output produced with the technology (e.g. the share of electricity produced from renewable sources) (Comin and Hobijn, 2004; Comin et al., 2006; Comin and Mestieri, 2013).

We favour the use of the intensive margin measure of renewable energy diffusion to the extensive measure primarily for two main reasons. First, the intensive measure is probably more directly related to climate change mitigation efforts than the share of adopters, since it reflects the extent to which energy systems are shifting towards clean sources and not just counting the number of adopters. And second, using a standard output of the technology (Bil kWh) provides more insights to understanding cross-country differences in production intensity more than just using the share of producers.

Table 1 provides the definitions and sources of the main variables we used. A number of standard control variables in the literature are used such as population size, GDP per capita and carbon dioxide emission. Literature has also pointed out to the role of income level and market size proxied by GDP per capita and population size respectively in adopting alternative energy sources (Aguirre and Ibikunle, 2014; Pfeiffer and Mulder, 2013). In addition, we control for the levels of CO_2 emissions, which can either have a positive or a negative effect on adoption of renewables depending on whether policy makers are conscious about environmental concerns or not (Aguirre and Ibikunle, 2014; Marques et al., 2011).

Fig. 1 graphically illustrates the trends in renewable energy observed in our dataset. Specifically, it shows that while the intensity of per capita net production of renewable electricity is increasing, the growth was uneven across different income groups during the analysed period (1980–2012). While the total renewable energy intensity is higher in developed countries, it has grown at a faster rate in lower- and upper-middle income countries. However, panel (c) also shows the (unweighted) average share of renewable energy as a proportion of the total energy production and consumption, which decreased over time. In general, this pattern can be explained by regulatory, social-cultural and market barriers which slow down diffusion (Sen and Ganguly, 2017; Ritchie and Roser, 2019). In our sample, the choice of an unweighted average may also drive this trend as in many of the analysed countries, demand for electricity has outpaced renewable energy production.

There are several approaches applied in the literature to define

"neighbourness" of a state (Mooney, 2001). The most standard one is using the proportion or number of countries sharing a border which adopted a certain policy (Biesenbender and Tosun, 2014; Lutz, 1987; Matisoff, 2008; Mooney, 2001; Stadelmann and Castro, 2014). Other authors have allowed for a more flexible definition of a neighbour by allowing countries to be as far as a certain defined threshold (ex. 100 Km) (Schaffer and Bernauer, 2014) or using the distance between capital cities or length of borders (MacGarvie, 2005).

A crucial part of our analysis rests on the construction of an index which reflects geographic proximity. As such we need an index that is capable of accounting both for the intensity of adoption in a given neighbouring country as well as the distance between the two countries. We primarily use one of the indices suggested by Comin et al. (2012), constructed as follows:
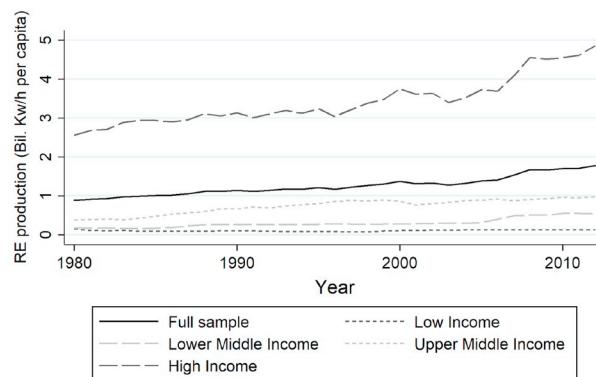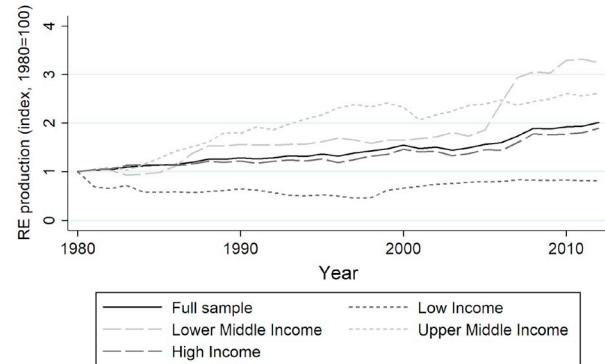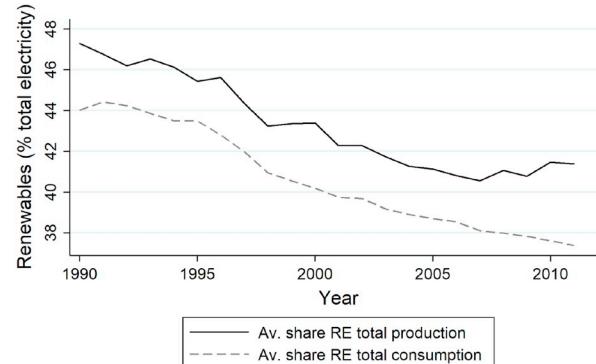
$$DIRE1_{it} = \sum_{j \neq i} \frac{int_{jt}}{dist_{ij}} \tag{1}$$

where $DIRE1_{it}$ is the distance-weighted index of renewable energy intensity we construct using bilateral distances and intensity of renewable energy in other countries. int_{jt} refers to the per capita intensity of production of electricity from renewable energy sources (in Bil. kWh) in country j at time t. $dist_{ij}$ refers to the geographical distance (in 1000 KM) between country i and j. In order to build this index for country i at time t we thus divide the intensity of electricity production per capita in country j at time t by the distance between country j and country i and then sum over all countries, with the exception of country i. Throughout this paper we use the per capita version of this index to increase the comparability of the measure between countries. This index is increasing in the intensity variable. However, it increases by a larger amount for countries closer to country i due to the shorter distance between countries i and j. As such our index links all the countries in our data set with each other, but the relative importance of other countries varies with distance. The exogeneity of such a variable can be plausibly advocated by the fact that it is a weighted average of the intensities in a large number of countries, each with a small share (Comin et al., 2012).

In addition to this, we also use an alternative index to test the robustness of our main conclusions. The alternative index we use is also proposed in Comin et al. (2012) and is defined as:

$$DIRE2_{it} = \sum_{j \neq i} int_{jt} * dist_{ij} \tag{2}$$

where index $DIRE2_{it}$ is simply the scalar product of the per capita intensity of electricity production from renewable energies in country j at time t and bilateral distance between the countries. This index is

(a) RE production intensity *per capita* by income group

(b) RE production intensity *per capita* by income group

(index)

(c) RE production and consumption (% total)

Notes: For panels (a) and (b) RE production intensity is expressed as Billion kWh *per capita*. Data on energy intensity is sourced from the EIA dataset and population data from the World Bank development indicators database.

Panel (a) displays the unweighted average for the countries included in the balanced sample. In panel (b), the same dependent variable is plotted, but it is index and assigned a value of 1 at the beginning of our data series (1980).

Panel (c) shows the percentage of renewable energy production and consumption as a proportion of the total. Once again, a simple unweighted average is used and only countries in the balanced sample are included.

Fig. 1. Renewable energy intensity, production and consumption over time. Notes: For panels (a) and (b) RE production intensity is expressed as Billion kWh per capita. Data on energy intensity is sourced from the EIA dataset and population data from the World Bank development indicators database. Panel (a) displays the unweighted average for the countries included in the balanced sample. In panel (b), the same dependent variable is plotted, but it is index and assigned a value of 1 at the beginning of our data series (1980). Panel (c) shows the percentage of renewable energy production and consumption as a proportion of the total. Once again, a simple unweighted average is used and only countries in the balanced sample are included.

increasing in the intensity of use of renewables in other countries but increases more for intensive use of renewables in more distant countries.[3]

Finally, we are also interested in examining the role of trade in accelerating the geographical pattern of technological diffusion since knowledge flows could be mapped through international trade patterns (Feldman, 1999). As such, we also build an index which weighs the distance-weighted index of renewables 1 (*DIRE*1) by the share of trade flow between the countries. The trade index 1 (*TRI*1) can be constructed as follows:

$$TRI1_{it} = \sum_{j \neq i} STF_{ijt} * \frac{int_{jt}}{dist_{ij}} \tag{3}$$

The trade index 1 is the sum of the interaction term between the share of the trade flow (*STF*$_{ijt}$)[4] between countries i and j at time t as a percentage of the total trade flow of country i and the distance-weighted index of renewable energy (DIRE 1) given by equation (2) for country i at time t.

For robustness checks, we also construct an alternative trade index 2 (*TRI*2) which is identical to (*TRI*1), but where the distance-weighted index of renewables for country i is given by equation (2). The trade index 2 is defined as:

[3] This point should be noted when comparing the results of Table 3 and A2. Distance-weighted index of renewables 1 (DIRE 1) uses distance as inverse but distance-weighted index of renewables 2 (DIRE 2)uses distance as a multiplicative.

[4] In this paper, trade flow is defined as the sum of imports and exports (in 1000 USD).

Table 2
Summary statistics.

Variables	N	Mean	S.d.	Min	Max
Population (millions)	3828	45.21	146.31	0.04	1350.70
GDP per capita (constant 2011)	3520	11358.34	16977.28	130.44	110001.1
Co2 emission per capita(metric tons)	3651	3.76	4.82	0.02	38.34
Electricity production from renewables (Bil. kWh)	3828	21.50	64.12	0.00	1003.52
Electricity production from renewables per capita (Billion kWh)	3828	1.25	3.91	0.00	54.33
DIRE index 1 (log) [a]	3828	3.57	0.66	2.26	6.22
DIRE index 2 (log) [b]	3828	7.07	0.36	6.17	8.17
Trade index 1 (log) [c]	2984	2.41	1.95	−6.69	8.52
Trade index 2 (log) [d]	2984	12.58	0.88	7.26	15.37
Electric power consumption growth rate (%)	2909	3.33	9.21	−56.03	120.78
Fossil Fuel energy consumption (% total)	3041	61.58	29.71	0	99.94
School enrollment, secondary (% gross)	2787	65.45	33.12	2.60	161.02
Kyoto	3828	0.29	0.45	0.00	1.00
RE policy	3828	0.35	0.48	0.00	1.00

[a] For each country i, Index 1 sums the per capita net renewable energy production in country j divided by the distance (in 1000 KM) between countries i and j for all j countries.
[b] DIRE index 2 stands for distance weighted index of renewable energy intensity. It is calculated as the sum of all pairwise multiplications of distance (in 1000 KM) and per capita renewable production.
[c] The trade index 1 weighs the DIRE index 1 by the bilateral trade share between countries.
[d] The trade index 2 weighs the DIRE index 2 by the bilateral trade share between countries.

$$TRI2_{it} = \sum_{j \neq i} STF_{ijt} * int_{jt} * dist_{ij} \tag{4}$$

Table 2 provides summary statistics of the main variables used in the paper. We use a panel of total renewable electricity net generation covering the (1980–2012) period with up to 116 countries when using the balanced sample and up to 163 countries when we used the unbalanced sample for robustness checks. The country coverage is entirely driven by the availability of data. As can be seen, the sample size for some variables varies due to missing data. For instance, for the trade index, data on trade pairs is only available until 2006. As a result, for this variable, we have fewer observations. In addition, where we control for other covariates as population, GDP per capita and CO_2 emissions, the sample size is reduced due to incomplete data for all countries during the period of study.

3.2. Method

In order to test for the role of geographic proximity on the intensity of renewable energy adoption, while controlling for unobserved heterogeneity, we use a fixed effect panel approach. Specifically we estimate the following model 5:

$$int_{it} = \alpha_i + \beta_{it}*T + \beta_{it}*T^2 + \beta_1 DIRE1_{it} + \beta_2 TRI_{it} + \beta_3 DIRE1_{it}*T + \gamma \mathbf{X_{it}}$$
$$+ e_{it} \tag{5}$$

where int_{it} denotes the log per capita intensity of net renewable electricity generation in country i at time t, α_i denotes a vector of country fixed effects to control for time-invariant country-specific heterogeneity, $\beta_{it}*T$ and $\beta_{it}*T^2$ denote a country-specific time trend and its quadratic form respectively to control for country-specific quadratic trends in the adoption of renewable energies (e.g. technical progress, policies) which may vary by country. $DIRE1_{it}$ is the distance weighted index of renewable energy intensity 1 derived in equation (1), $TRI1_{it}$ is the trade index derived in equation (3), $\mathbf{X_{it}}$ denotes a vector of controls which depend on the specification used in section 4. e_{it} is a stochastic error term. All our explanatory variables are in logarithmic form, and thus coefficients are interpreted as elasticities.

Regarding the expected signs of the coefficients in equation (5) for the main independent variables, we have three expectations. First, since we argue that geographical proximity is likely to play a role in the inter-country diffusion of technologies, we would expect that the β_1 coefficient on the distance weighted index of renewable energy intensity ($DIRE1_{it}$) to be positive.[5] The second hypothesis relates to the trade channel. We would expect a positive coefficient for our trade index ($TRI1_{it}$) since a stronger effect of diffusion is likely to be observed if a trade partner is an intensive adopter of the technology. The third hypothesis related to the importance of geographical proximity over time is captured by the coefficient on the interaction term ($DIRE1_{it}*T$). The sign of this coefficient could either be positive or negative depending on which part of the S-curve renewables adoption currently is. As such, β_3 will be positive if countries are in the accelerating phase of adoption of renewables (i.e the initial part of S-curve) and negative if the adoption rate is decelerating.

4. Main results and discussion

Table 3 presents the main results. The dependent variable is log per capita total renewable electricity net generation, excluding hydro(Bil kWh). The distance index refers to DIRE1 which is the log of the sum of per capita intensity of renewable electricity production in country j divided by the distance between countries i and j (in 1000 KM) for all j countries.

Regarding the importance of geographical proximity to adopters, the main variable of interest (DIRE1 index) is consistently positive (as expected) and statistically significant at the 1% level in all model specifications of Table 3. The magnitude of the effect of geographical proximity is even stronger in column (9), when other covariates (GDP per capita and population), country-specific trends, country and time fixed effects are included. This provides strong support for the effect of the geographical proximity as a key driver of adoption of renewable energy in our sample.

We also test whether the effect of geographical proximity becomes more important given trade links with intensive adopters of renewable energy technology. In terms of the trade index in Table 3, it also displays the hypothesized sign in every specification, and is statistically significant at the 5% level at two of the three specifications. The latter suggest that, in addition to a positive spatial diffusion of intensity of

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[5] In the case of using the alternative index $DIRE2_{it}$, the expected sign of the coefficient is negative since the index is a product of distance and intensity of adoption.

Table 3
Main results - Intensity renewable energy production per capita.

Variables	Dependent variable: Log renewable production per capita								
	1	2	3	4	5	6	7	8	9
DIRE index 1 (pc, log)	2.475*** (0.360)	2.309*** (0.352)	2.457*** (0.456)	2.418*** (0.341)	2.733*** (0.649)	2.717*** (0.707)	2.532*** (0.302)	2.954*** (0.603)	3.170*** (0.680)
DIRE index 1 (pc, log) * Trend		0.016** (0.007)	0.016* (0.008)		−0.023 (0.027)	−0.031 (0.038)		−0.032 (0.027)	−0.05 (0.038)
Trade index (pc, log)			0.069** (0.033)			0.022** (0.011)			0.017 (0.012)
Population (log)							2.205 (2.026)	2.19 (2.001)	0.996 (1.346)
GDP pc (log)							0.316*** (0.146)	0.309** (0.144)	0.2 (0.147)
Co2 emissions pc (log)							0.079 (0.060)	0.081 (0.061)	0.085 (0.062)
Constant	−9.740*** (1.156)	−9.263*** (1.122)	−9.781*** (1.430)	−9.629*** (1.060)	−10.559*** (1.964)	−10.467*** (2.091)	−17.089*** (5.507)	−18.240*** (5.896)	−15.521*** (4.682)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	3828	3828	2970	3828	3828	2970	2976	2976	2430
Number of periods per country	33	33	27	33	33	27	32	32	27
Number of countries	116	116	110	116	116	110	93	93	90
R-squared (within)	0.369	0.397	0.358	0.798	0.799	0.796	0.799	0.8	0.802

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent clustered standard errors at the country level. All numbers in the table were rounded to 3 decimal places. All specifications use a balanced sample for the variables included in the specification. For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006.

For all specifications that include country-specific trends, we include a quadratic trend.

renewables, this effect is stronger when main trade partners are also intensive adopters of renewable energies. This finding is in line with literature where international trade plays a crucial role in technology diffusion, as it increases a country's exposure to innovations and the capability to absorb new technologies (Eaton and Kortum, 2002).

With regards to the interaction of the trend with the distance weighted index of renewable energy, it serves to capture if the importance of spatial interdependence changes over time or not. We note that the significance and the sign of the coefficient of the interaction term (*DIRE*1 *Trend) of Table 3 is not robust to different model specifications. In columns 2 and 3, we note that it is positive and significant at the 5% or 10% level, which suggests that the effect of spatial interdependence slightly increases over time. However, once country-specific trends are controlled for, the coefficient of the interaction term loses significance and is negative, supporting our initial hypothesis. There are two possible explanations regarding why this result is weaker for renewable energies compared to other technologies. First, in many countries the technology is still in its formative phase (Bento et al., 2018), which is often characterised by uncertainties, testing and creating suitable market conditions before mass commercialisation of the technology. Secondly, since the dependent variable captures electricity generation from a number of different renewable energy technologies, some technologies may be at an advanced stage whereas others may still be in their formative phase in the analysed countries.

With regards to the controls used, consistent with literature on adoption of renewable energy technologies, countries with higher income per capita are more likely to adopt renewable sources for electricity generation (Aguirre and Ibikunle, 2014; Eyraud et al., 2011). A larger domestic market size proxied by population size does not seem to play a role in the intensity of diffusion on renewable energy as the coefficient on population is insignificant, consistent with some findings in the literature (Eyraud et al., 2011). Despite the positive coefficient on the carbon emissions variable which indicates the effect of environmental concerns on adopting alternative clean energy sources, it is nonetheless insignificant.

Regarding the validity of our results, given the correlation between geography and certain renewable energies (e.g. solar), one could argue that the effect captured by the geographical proximity variable could also be capturing the effects of a number of unobserved variables. The approach we use in this paper is able to partially account for this through the inclusion of fixed effects. In addition to this, as argued in Comin et al. (2012), our index choice is also likely to address the potential issue of the endogeneity of the geographical proximity index as each country carries a small weight in the index and because, under the Null hypothesis (of no effect of proximity), the tests are still valid.

However, there is still the possible existence of omitted variable bias. We try to minimize this by including country-specific fixed effects (that deal with time-invariant country-specific unobservable factors), year fixed effects (that deal with time-specific unobservable factors that affect the whole sample) and country-specific quadratic time trends that account for the different pattern of diffusion in different countries. We also show in the appendix that our main results are robust to the inclusion of additional control variables. However, we are not able to control for all variables that could potentially affect the diffusion and, as such, while we argue that our approach reduces the risk of our results being driven by omitted variable bias, its existence can never be completely ruled out.

4.1. Robustness checks

We conducted six robustness checks. First, we estimated the model using the unbalanced sample in Table A1 in appendix. The sample size includes a larger set of countries that ranges between 144 and 163 countries. Overall, we find that the sign and magnitude of the distance index remain similar. However, while the significance of the index interaction with trend is positive and significant throughout most

specifications, the trade index is only statistically significant in column 3.

Following Comin et al. (2012), Table A2 presents the results using the alternative Distance index 2 .[6] Since it is a multiplicative function of distance, as hypothesized, the sign of the coefficient is the opposite of those obtained using our main index. We find a statistically significant relationship in all specifications where we exclude interactions. When interactions are included the effects are still similar in terms of magnitude, but no longer statistically significant.

Third, there are often time lags in the adoption of technology as countries are unlikely to instantaneously react to adoption patterns of neighbouring countries. As a result, we test the sensitivity of our results by running regressions using a one or two years lag of our distance weighted index of renewable energy intensity. Regression results are presented in Table A3. We note that the index has a positive and significant effect in all our specifications. In addition, we also note that the interaction with the trend becomes negative and significant when trends and controls are included. However, the trade index becomes insignificant.

The pattern of adoption of renewable energy may be spatially correlated between observation. As a result, we estimate the model adjusting the standard errors to account for spatial autocorrelation and heteroskedasticity. Moreover, the estimates of the country-specific serial correlation are estimated to decay to zero after a lag of 3 years. This method adjusts the standard errors to control for heteroskedasticity, county-specific serial correlation as well as cross-sectional spatial correlation, Hsiang (2010). Table A4 reports the results and the main findings remain unchanged. The coefficient on the DIRE1 index remains positive and significant after controlling for spatial correlation. In addition the trade index as well as the trend interaction with the distance index are positive and significant across all specifications.

We disaggregate the sample using the World Bank income classification. Table A5 shows the results of the regression where each income group is expressed in two columns. The distance index is positive and significant across all income groups except for low-income and the results suggest heterogeneity in terms of the coefficients, which are highest in upper and lower-middle income countries. There are at least two possible explanations for the insignificant effect of geographical proximity in low income countries. First, since countries in the same income level tend to be geographically clustered and that adoption rates observed in low income countries are low, (see Fig. 1), there may be no considerable stock of knowledge in neighbouring countries. Second, renewable electricity in a number of low income countries comes from hydro power plants (World Bank, 2018), which is not captured by our dependent variable since it excludes hydro sources. The trade interaction is positive and statistically insignificant for all the sub-samples, but higher in low-middle income countries. High income countries display a positive interaction with time, whereas other income groups display an insignificant negative interaction.

Finally, in Table A6 we add a set of controls that have been included in other studies and which could be associated with the diffusion of renewable energy technologies (Pfeiffer and Mulder, 2013) where columns (1–3) include the independent variables in levels and columns (4–6) the variables are lagged by one year. These variables include schooling levels, renewable energy policy instruments (economic and regulatory), kyoto protocol ratification, growth in electricity consumption and fossil fuel dependence. We find that our main results remain when controlling for other factors. We also find no evidence that the either the implementation of policy instruments or the ratification of Kyoto protocol accelerate the diffusion of green technologies. In contrast, high share of electricity production from fossil fuel sources is statistically significant and negative across all models specifications.

5. Conclusion and policy implications

In this paper, we argue that in the context of renewable energy technology, the diffusion of the technology is affected by the adoption pattern of neighbouring countries and is accentuated by trade relations with intensive adopters of the technology. In examining the effect of geographical proximity to adopters on the diffusion of renewable energies, we constructed two indexes such that the intensity of technology adoption in one country is a function of (1) geographical proximity to an intensive adopter (distance-weighted index of renewable energy intensity), and (2) higher bilateral trade flows (trade index).

From a methodological perspective, we believe the empirical method employed in this paper represents an improvement on previous attempts to quantify the effect of geographic proximity in the policy diffusion literature. By failing to control for time-invariant country characteristics, the geographic diffusion variables could actually be capturing an average effect of a number of different factors. Also, as discussed in Mooney (2001), many of the early studies on policy diffusion provided biased estimates of neighbouring effects. According to the author, these biases were a consequence of the choice of the regional effect variable (share of neighbours adopting a policy) and the statistical method applied (often event history analysis), which did not account for country-specific effects and trends. The methodology we use represents an improvement as the geographic proximity variable and the estimation method we use allow us to account for country fixed-effects and country-specific trends.

The results bear a number of implications. First, they show that, in terms of the role of geographical proximity to adopters, renewable energies seem to exhibit the same pattern as other technologies (Comin et al., 2012). Second, it thus follows that, to a certain extent, we can expect geographical spillovers in the diffusion of renewable energies to occur. Nevertheless, the potential effect of this geographical spillover is inconclusive over time. As such, domestic policies actively promoting the diffusion of renewable energies are likely to remain important. Third, the findings of this paper highlight the importance of trade links with adopters of renewables as catalyst of the diffusion of renewable energies. Economic policies towards innovation and environmental sustainability, can become more effective if they focus on strengthening ties with trade partners or neighbouring countries who had a successful experience implementing policies to encourage the diffusion of the new technology. As such, lowering trade barriers especially in developing countries is likely to trigger faster diffusion of renewable energy technologies, where we find a lower spatial diffusion of technology. This could be reflecting either a low amount of technology-specific knowledge in neighbouring countries, capital constraint, inadequate policy support or other hurdles. In other words, countries may be able to observe the technology being adopted successfully, but not being able to replicate this domestically.

However, our results with regards to the spatial diffusion of renewable energies also highlight a number of areas for future research. First, while our paper finds an effect of geographic proximity to intensive adopters on overall renewable energy intensity, it is not able to assess how these patterns differ across different sources of renewable energies. Given the different nature of each source of renewable energies in terms of its prospects, marketability and challenges, each source might have a different adoption pattern. Second, while we find differentiated results of spatial diffusion by income level, further analysis could be undertaken to further investigate the determinants of this heterogeneous diffusion pattern. Finally, we tried to capture how interactions between countries, proxied by trade relations, can affect the diffusion of technology adoption in the case of renewable energies. However, future work could further explore whether certain types of interaction have a more pronounced effect on technology diffusion.

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[6] Given by the logarithm of the sum of the product of per capita total renewable electricity net generation in country i and bilateral distance between country i and country j, for all j countries.

Appendix

Table A1
Robustness check 1 - renewable energy production *pc*, unbalanced panel.

Variables	Dependent variable: Log renewable production per capita, unbalanced								
	1	2	3	4	5	6	7	8	9
DIRE index 1 (pc, log)	2.481*** (0.328)	2.298*** (0.323)	2.443*** (0.423)	2.497*** (0.279)	2.177*** (0.534)	2.151*** (0.500)	2.749*** (0.257)	2.307*** (0.372)	2.569*** (0.333)
DIRE index 1 (pc, log) * Trend		0.017** (0.007)	0.016** (0.008)		0.023 (0.027)	0.018 (0.028)		0.034** (0.017)	0.016 (0.014)
Trade index (pc, log)			0.068** (0.031)			0.031 (0.020)			−0.004 (0.012)
Population (log)							−0.335 (0.403)	0.433 (0.391)	0.351 (0.338)
GDP pc (log)							0.189 (0.131)	0.176 (0.130)	0.237* (0.124)
Co2 emissions pc (log)							0.008 (0.050)	0.063 (0.054)	0.043 (0.044)
Constant	−10.048*** (1.070)	−9.530*** (1.044)	−10.028*** (1.347)	−10.137*** (0.885)	−9.201*** (1.605)	−9.055*** (1.467)	−11.830*** (1.681)	−11.973*** (1.660)	−12.945*** (1.523)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	4628	4628	3518	4628	4628	3518	4068	4068	3214
Number of periods per country	28.393	28.393	23.453	28.393	28.393	23.453	26.416	26.416	22.319
Number of countries	163	163	150	163	163	150	154	154	144
R-squared (within)	0.341	0.37	0.352	0.687	0.69	0.741	0.687	0.694	0.742

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent clustered standard errors at the country level. All numbers in the table were rounded to 3 decimal places.
For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006. For all specifications that include country-specific trends, we include a quadratic trend.

Table A2
Robustness check 2 - alternative index, logs.

Variables	Dependent variable: Log renewable production per capita								
	1	2	3	4	5	6	7	8	9
DIRE index 2 (pc, log)	−3.155*** (0.847)	−2.788** (1.089)	−1.442 (1.031)	−1.042** (0.480)	−0.792 (1.074)	−0.884 (1.062)	−1.290** (0.562)	−1.018 (1.048)	−1.574 (1.156)
DIRE index 2 (pc, log) * Trend		−0.006 (0.015)	−0.001 (0.019)		−0.023 (0.076)	0.03 (0.076)		−0.024 (0.075)	0.077 (0.084)
Trade index 2 (pc, log)			−0.015 (0.028)			0.009 (0.018)			0.01 (0.022)
Population (log)							2.665 (2.622)	2.659 (2.612)	1.529 (2.182)
GDP pc (log)							0.444** (0.179)	0.443** (0.177)	0.327* (0.182)
Co2 emissions pc (log)							0.048 (0.064)	0.047 (0.064)	0.022 (0.072)
Constant	19.131*** (5.609)	16.725** (7.168)	7.937 (6.840)	4.909 (3.196)	3.399 (6.682)	3.497 (6.624)	−2.539 (6.300)	−4.157 (9.575)	1.925 (7.881)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	3828	3828	2970	3828	3828	2970	2976	2976	2430
Number of periods per country	33	33	27	33	33	27	32	32	27
Number of countries	116	116	110	116	116	110	93	93	90
R-squared (within)	0.181	0.182	0.108	0.752	0.752	0.751	0.748	0.748	0.752

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent clustered standard errors at the country level. All numbers in the table were rounded to 3 decimal places.
For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006. For all specifications that include country-specific trends, we include a quadratic trend.

Table A3
Robustness check 3 - lagged index values.

Variables	Dependent variable: Log renewable production per capita														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lag 1 DIRE index 1 (pc, log)	2.107*** (0.336)	1.936*** (0.329)	2.022*** (0.438)	1.346*** (0.334)	1.960*** (0.642)	2.074** (0.812)	1.446*** (0.287)	2.103*** (0.581)	2.412*** (0.744)						
Lag 2 DIRE index 1 (pc, log)										1.798*** (0.287)	1.618*** (0.376)	0.601** (0.260)	1.648** (0.711)	1.347** (0.597)	1.757** (0.719)
Lag 1 DIRE index 1 (pc) * Trend		0.016** (0.007)	0.015* (0.009)		−0.043 (0.027)	−0.092 (0.056)		−0.047* (0.028)	−0.105* (0.055)						
Lag 1 trade index (pc, log)			0.062* (0.034)			0.014 (0.013)			0.005 (0.014)						
Lag 2 trade index (pc, log)											0.056 (0.035)		0.013 (0.015)		0.005 (0.016)
Lag 2 DIRE index 1 (pc) * Trend											0.015* (0.009)		−0.127** (0.056)	−0.045 (0.032)	−0.126** (0.056)
Population (log)							2.628 (2.518)	2.599 (2.446)	1.651 (1.969)					2.625 (2.839)	1.888 (2.431)
GDP pc (log)							0.350** (0.135)	0.326** (0.127)	0.218 (0.146)					0.330*** (0.119)	0.222 (0.146)
Co2 emissions pc (log)							0.043 (0.062)	0.05 (0.064)	0.053 (0.071)					0.038 (0.067)	0.037 (0.081)
Constant	−8.558*** (1.086)	−8.117*** (1.047)	−8.431*** (1.376)	−6.334*** (1.034)	−8.027*** (1.869)	−8.184*** (2.216)	−15.025** (6.671)	−16.576** (6.842)	−14.473** (6.175)	−7.573*** (0.936)	−7.183*** (1.178)	−4.100*** (0.792)	−6.530*** (1.747)	−14.392* (7.630)	−12.839* (7.031)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	3712	3712	2860	3712	3712	2860	2883	2883	2340	3596	2750	3596	2750	2790	2250
Number of periods per country	32	32	26	32	32	26	31	31	26	31	25	31	25	30	25
Number of countries	116	116	110	116	116	110	93	93	90	116	110	116	110	93	90
R-squared (within)	0.319	0.349	0.293	0.763	0.764	0.752	0.758	0.76	0.755	0.283	0.243	0.746	0.736	0.737	0.734

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent clustered standard errors at the country level. All numbers in the table were rounded to 3 decimal places. For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006. For all specifications that include country-specific trends, we include a quadratic trend.

Table A4
Robustness check 4 - adjusting for spatial autocorrelation using balanced sample.

Variables	Dependent variable: Log renewable production per capita								
	1	2	3	4	5	6	7	8	9
DIRE index 1 (pc, log)	2.475*** (0.042)	2.477*** (0.044)	2.713*** (0.049)	2.418*** (0.078)	2.748*** (0.081)	2.775*** (0.099)	2.562*** (0.091)	2.888*** (0.098)	3.050*** (0.114)
DIRE index 1 (pc, log) * Trend		0 (0.000)	0.001*** (0.000)		0.002*** (0.000)	0.002*** (0.000)		0.002*** (0.000)	0.002*** (0.000)
Trade index (pc, log)			0.073*** (0.006)			0.022*** (0.007)			0.015* (0.008)
Population (log)							2.036*** (0.440)	1.714*** (0.433)	0.739* (0.443)
GDP pc (log)							0.342*** (0.069)	0.330*** (0.069)	0.161* (0.093)
Co2 emissions pc (log)							0.078*** (0.026)	0.060** (0.026)	0.064** (0.030)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	3828	3828	2970	3828	3828	2970	3366	3366	2708
R-squared (within)	0.246	0.246	0.269	0.744	0.75	0.762	0.75	0.756	0.765

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent standard errors that account for spatial correlation (uniformly weighted up to 1000 km) and country-specific serial correlations using a Bartlett window of 3 years. All numbers in the table were rounded to 3 decimal places.
For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006. For all specifications that include country-specific trends, we include a quadratic trend.

Table A5
Robustness check 5 - disaggregating by income groups using balanced sample.

Variables	Dependent variable: Log renewable production per capita							
	High	High	Upper middle	Upper middle	Lower middle	Lower middle	Low income	Low income
DIRE index 1 (pc, log)	1.473*** (0.506)	1.428*** (0.449)	2.992*** (0.618)	2.763*** (0.709)	3.491*** (1.095)	4.169*** (1.023)	3.592 (3.204)	3.335 (2.953)
DIRE index 1 (pc, log) * Trend	0.024 (0.021)	0.028 (0.025)	−0.021 (0.031)	−0.008 (0.041)	−0.048 (0.055)	−0.107* (0.061)	−0.133 (0.110)	−0.224 (0.210)
Trade index (pc, log)		0.036 (0.022)		0.004 (0.015)		0.023 (0.025)		0.074 (0.062)
Constant	−6.320*** (1.856)	−6.062*** (1.564)	−10.853*** (1.811)	−10.210*** (2.064)	−12.350*** (2.922)	−14.094*** (2.672)	−12.991 (8.476)	−12.137 (7.642)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	1089	783	1056	864	1056	837	627	486
Number of periods per country	33	27	33	27	33	27	33	27
Number of countries	33	29	32	32	32	31	19	18
R-squared (within)	0.911	0.875	0.796	0.766	0.852	0.864	0.601	0.714

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent standard errors. All numbers in the table were rounded to 3 decimal places.
For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006.
For all specifications that include country-specific trends, we include a quadratic trend. Countries are classified to four groups according to World Bank income classification using the Atlas method, where low-income economies are those with a GNI per capita of 1,005 or less; lower middle-income economies are those with a GNI per capita between 1,006 and 3,955; upper middle-income economies are those with a GNI per capita between 3,956 and 12,235; high-income economies are those with a GNI per capita of 12,236 or more (World Bank, 2018).

Table A6
Robustness check 6 - using more control variables using unbalanced sample.

Variables	Dependent variable: Log renewable production per capita					
	Using level (t)			Using lags (t-1)		
DIRE index 1 (pc, log)	2.141*** (0.353)	2.060*** (0.382)	2.276*** (0.409)	1.431*** (0.364)	1.187*** (0.401)	1.198*** (0.448)
Population (log)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	−0.093 (0.518)	0.544 (0.460)	0.993* (0.519)
GDP pc (log)	0.000** (0.000)	0.000* (0.000)	0.000* (0.000)	0.532** (0.217)	0.582*** (0.221)	0.607** (0.238)
Co2 emissions pc (log)	0.026 (0.024)	0.034 (0.024)	0.012 (0.022)	0.001 (0.072)	0.071 (0.080)	0.079 (0.058)
Electricity consumption growth (%)	0.13 (0.117)	0.129 (0.120)	0.228 (0.170)	0.188 (0.163)	0.218 (0.160)	0.374* (0.218)

Table A6 (*continued*)

Variables	Dependent variable: Log renewable production per capita					
	Using level (t)			Using lags (t-1)		
Electricity from fossil (% of total)	−0.020*** (0.004)	−0.019*** (0.004)	−0.018*** (0.003)	−0.016*** (0.004)	−0.015*** (0.004)	−0.014*** (0.004)
Enrollment, secondary (% gross)	0.005** (0.002)	0.005** (0.002)	0.005* (0.003)	0.003 (0.003)	0.003 (0.002)	0.002 (0.003)
kyoto (dummy)	0.021 (0.049)	0.019 (0.047)	0.039 (0.059)	−0.016 (0.046)	−0.019 (0.046)	0.016 (0.046)
Renewable Energy Policy (dummy)	−0.013 (0.090)	−0.019 (0.094)	0.033 (0.094)	−0.045 (0.090)	−0.068 (0.088)	0.006 (0.093)
DIRE index 1 (pc, log) * Trend		0.006 (0.009)	−0.001 (0.008)		0.017** (0.008)	0.019* (0.010)
Trade index (pc, log)			0.076 (0.053)			0.06 (0.050)
Constant	−8.470*** (1.222)	−8.259*** (1.282)	−9.118*** (1.385)	−10.135*** (2.706)	−11.504*** (2.645)	−12.954*** (2.896)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific trend	No	No	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observation	2511	2511	1972	2521	2521	1979
Number of periods per country	21.28	21.28	17.451	21.185	21.185	17.513
Number of countries	117	117	112	118	118	112
R-squared (within)	0.437	0.438	0.425	0.367	0.384	0.345

*, **, *** deonte statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses represent standard errors. All numbers in the table were rounded to 3 decimal places.

For the specifications where we use the trade index as a control we lose 6 years of data as the data for pairwise trade flows were only available until 2006.

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